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| EXAMINER | |
|---|---|
| DAY, HERNG DER | |
| **ART UNIT** | **PAPER NUMBER** |
| 2123 | 17 |

DATE MAILED: 08/12/2003

Please find below and/or attached an Office communication concerning this application or proceeding.

| Office Action Summary | Application No. | Applicant(s) |
|---|---|---|
| | 09/282,619 | CUNG ET AL. |
| | Examiner | Art Unit |
| | Herng-der Day | 2123 |

-- *The MAILING DATE of this communication appears on the cover sheet with the correspondence address* --

**Period for Reply**

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133).
- Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

**Status**

1)☒ Responsive to communication(s) filed on *27 May 2003* .

2a)☒ This action is **FINAL**. 2b)☐ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

**Disposition of Claims**

4)☒ Claim(s) *1,3-6 and 13-25* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1, 3-6, 13-25* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

**Application Papers**

9)☐ The specification is objected to by the Examiner.

10)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

11)☐ The proposed drawing correction filed on _____ is: a)☐ approved b)☐ disapproved by the Examiner.

If approved, corrected drawings are required in reply to this Office action.

12)☐ The oath or declaration is objected to by the Examiner.

**Priority under 35 U.S.C. §§ 119 and 120**

13)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____ .

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

14)☐ Acknowledgment is made of a claim for domestic priority under 35 U.S.C. § 119(e) (to a provisional application).

a) ☐ The translation of the foreign language provisional application has been received.

15)☐ Acknowledgment is made of a claim for domestic priority under 35 U.S.C. §§ 120 and/or 121.

**Attachment(s)**

1) ☐ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO-1449) Paper No(s) _____ .
4) ☐ Interview Summary (PTO-413) Paper No(s). _____ .
5) ☐ Notice of Informal Patent Application (PTO-152)
6) ☐ Other: .

## DETAILED ACTION

1. This communication is in response to Applicants' Amendment (paper # 16) to Office Action dated February 25, 2003 (paper # 15), mailed May 27, 2003.

1-1. Claims 22-24 have been amended; claims 1, 3-6, and 13-25 are pending.

1-3. Claims 1, 3-6, and 13-25 have been examined and claims 1, 3-6, and 13-25 have been rejected.

### *Claim Rejections - 35 USC § 103*

2. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

3. Claims 1, 5-6, 13-15, 18-22, and 25 are rejected under 35 U.S.C. 103(a) as being unpatentable over Piatetsky-Shapiro, "Discovery, Analysis, and Presentation of Strong Rules", in "Knowledge Discovery in Database", AAAI/MIT Press, 1991, in view of Simoudis et al., U.S. Patent No. 5,692,107 issued on November 25, 1997.

Piatetsky-Shapiro discloses KID3 Algorithm for discovery of exact rules. "At the end, a cell for A=a contains the summary of all the file tuples satisfying A=a" (page 235, line 34). The summary may preserve all of the field values and their relation to one another because "what intermediate information has to be kept is determined by the type of the summary description we want to have at the end" (page 236, lines 6-8). Therefore, one of ordinary skill in the art would

be able to obtain a target group with one or more desired attributes and respective values, for example, A=a and B=b, by applying KID3 Algorithm and setting the summary to collect all the information of every sample which satisfying A=a and B=b within the sample population.

Piatetsky-Shapiro also discloses how to precompute field statistics (page 230, line 19) to get information such as "How many samples satisfy the condition of C=c?" (page 233, lines 13-16) in the sample population. With these statistics, the cardinality |C| of conditions C=c can be estimated efficiently and accurately (page 233, lines 19-20).

Besides, Piatetsky-Shapiro teaches that "the typical rule-discovery task is to find K rules with the highest rule-interest function" (page 231, line 28). "Usually, the interest of rule A → B is computed as a function of p(A), the probability of A; p(B); p(A&B); rule complexity, and, possibly, other parameters, such as the mutual distribution of A and B or the domain sizes of A and B" (page 231, lines23-26). The simplest function that Piatetsky-Shapiro suggested is |A&B| - (|A||B|/N) (page 232, line 18).

The following example serves to explain what information and knowledge Piatetsky-Shapiro has disclosed. Let N be the total number of samples. A, B, C, D, and E are attributes of each sample. The target group is all the samples with A=a and B=b. To find out which attribute of C, D, or E, or which attribute value of e1 or e2, is more sensitive for the purpose of generating a predictive model, one of ordinary skill in the art would be motivated by applying Piatetsky-Shapiro's algorithm for the following rules:

(A=a and B=b) → (C=c)

(A=a and B=b) → (D=d)

(A=a and B=b) → (E=e1) and (A=a and B=b) → (E=e2)

Next, |(A=a and B=b) & (C=c)|, |(A=a and B=b) & (D=d)|, |(A=a and B=b) & (E=e1)|, and |(A=a and B=b) & (E=e2)| are calculated. Statistics of |(A=a and B=b)|, |(C=c)|, |(D=d)|, |(E=e1)|, and |(E=e2)| are precomputed. By using the simplest rule-interest function as Piatetsky-Shapiro suggested, a simple statistical measure will be calculated. Using a different rule-interest function, such as an entropy function, may generate a different statistical measure.

**3-1.** Regarding claims 1 and 5-6, Piatetsky-Shapiro discloses a method of reducing the number of the number of attributes and respective values of a sample population employed in generating a predictive model, said method comprising the steps of:

obtaining one or more desired attributes and respective values (A=a, page 235, line 3);

comparing said one or more desired attributes and respective values with said sample population to obtain a target population (KID3 Algorithm and summary, page 235, lines 21-34);

determining a statistical measure of difference (rule-interest measures, section 13.3; and the simplest function, page 232, line 18) between each of the attributes and respective values of said target population (KID3 Algorithm, page 235, lines 21-34) and the attributes and respective values of the sample population (Precomputing Field-Value Statistics, section 13.4).

Piatetsky-Shapiro fails to expressly disclose the details of utilizing the statistical measure of difference to reduce the number of attributes and respective values of said sample population, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

(claim 1) utilizing said statistical measure of difference to reduce the number of attributes and respective values of said sample population (a predictive model is extracted based on data mining results, column 4, lines 52-53);

(claim 5) identifying a predetermined percentage of attributes and respective values having a larger statistical measure of difference than remaining attributes and respective values (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48);

(claim 6) identifying attributes and respective values where said statistical measure of difference exceeds a predetermined amount (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claims 1 and 5-6 because Simoudis et al. disclose details of a very flexible data mining method, for example, several different modules

implementing different data mining techniques to choose from, for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**3-2.** Regarding claim 13, Piatetsky-Shapiro discloses a method of selecting attributes for computing a model, comprising:

for a plurality of samples each having values for a plurality of attributes (Extending KID3 to Complex Conditions, section 13.5.3, page 237):

for each of the plurality of attributes:

comparing the attribute values for a target group of samples to the attribute values for all of the plurality of samples (KID3 Algorithm, page 235, lines 21-34); and

determining a difference between the attribute values for the target groups and the attribute values for all of the plurality of samples (the simplest function, page 232, line 18).

Piatetsky-Shapiro fails to expressly disclose the details of identifying and selecting attributes, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a

statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

identifying attributes; within the plurality of attributes having a largest difference between the attribute values for the target groups and the attribute values for all of the plurality of samples (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48); and

selecting at least some of the identified attributes (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claim 13 because Simoudis et al. disclose details of a very flexible data mining method for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**3-3.** Regarding claims 14 and 18-19, Piatetsky-Shapiro discloses a system for selecting attributes for computing a model, comprising:

a memory containing data for a plurality of samples each having values for a plurality of attributes (Extending KID3 to Complex Conditions, section 13.5.3, page 237); and

a processor coupled to the memory and executing a selection process including:

comparing attribute values for samples having a desired attribute value to attribute values for all samples (KID3 Algorithm, page 235, lines 21-34);

Piatetsky-Shapiro fails to expressly disclose the details of selecting a subset of available attributes and employing the selected subset of attributes to generate a predictive model, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

(claim 14) selecting a subset of available attributes based on a difference between attribute values for the samples having the desired attribute value and attribute values for all of the samples (results, column 4, lines 48-51); and

(claim 14) employing the selected subset of attributes to generate a predictive model (a predictive model is extracted based on data mining results, column 4, lines 52-53);

(claim 18) identifies a predetermined percentage of attributes having a larger difference in the attribute values for selection (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48);

(claim 19) identifies, for selection, attributes having a difference in the attribute values exceeding a predetermined amount (user's queries or hypotheses set module-specific parameters, column 4, lines 45-48).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claims 14 and 17-19 because Simoudis et al. disclose details of a very flexible data mining method for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**3-4.** Regarding claim 15, Piatetsky-Shapiro further discloses that the selection process determines a statistical measure of difference between the attribute values for samples having the desired attribute and the attribute values for all of the samples (the simplest function, page 232, line 18).

**3-5.** Regarding claim 20, Piatetsky-Shapiro discloses a system for computing a model, comprising:

a memory containing data for a plurality of samples each having values for a plurality of attributes (Extending KID3 to Complex Conditions, section 13.5.3, page 237); and

a processor coupled to the memory and executing a selection process including:

comparing attribute values for a target subset of the plurality of samples to attribute values for all of the samples (KID3 Algorithm, page 235, lines 21-34);

Piatetsky-Shapiro fails to expressly disclose the details of selecting attributes and computing a model, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

selecting attributes having a largest difference between attribute values for the target subset and attribute values for all of the samples (results, column 4, lines 48-51); and

computing a model employing the selected attributes (a predictive model is extracted based on data mining results, column 4, lines 52-53).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claim 20 because Simoudis et al. disclose details of a very flexible data mining method for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**3-6.** Regarding claims 21 and 22, Piatetsky-Shapiro discloses a computer usable medium for selecting attributes for computing a model, said computer usable medium comprising:

computer program code for reading values of attributes for a plurality of samples (Extending KID3 to Complex Conditions, section 13.5.3, page 237);

computer program code for comparing attribute values for samples having a desired attribute value to attribute values for all samples (KID3 Algorithm, page 235, lines 21-34); and

Piatetsky-Shapiro fails to expressly disclose the details of selecting a subset of available attributes and determining a statistical measure of difference, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a

statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

(claim 21) computer program code for selecting a subset of available attributes based on a difference between attribute values for samples having the desired attribute value and attribute values for all samples (results, column 4, lines 48-51);

(claim 22) computer program code for determining a statistical measure of difference between the attribute values for samples having the desired attribute value and the attribute values for all samples (the simplest function, page 232, line 18).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claims 21 and 22 because Simoudis et al. disclose details of a very flexible data mining method for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**3-7.** Regarding claim 25, Piatetsky-Shapiro discloses a computer usable medium for selecting attributes for computing a model, said computer usable medium comprising:

computer program code for comparing attribute values for a target group of samples to attribute values for all samples for each of a plurality of attributes (KID3 Algorithm, page 235, lines 21-34);

computer program code for determining a difference between the attribute values for the target group of samples and the attribute values for all of the samples (the simplest function, page 232, line 18); and

Piatetsky-Shapiro fails to expressly disclose the details of selecting a group of attributes, although Piatetsky-Shapiro discloses that patterns of full data set can be estimated by sample-derived rules with an estimated accuracy (Abstract), i.e., a predictive model of full data set can be generated by sample-derived rules with an estimated accuracy. Nevertheless, Piatetsky-Shapiro does suggest that rules are part of the domain knowledge (page 230, line 12) and domain knowledge can be used to improve on purely statistical prediction (page 230, line 26).

Simoudis et al. teaches the selection of a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25), for example, a statistical module, to perform data mining to the selected data set to gain domain knowledge (for example, collection of rules, column 4, lines 53-55). The user sets module-specific parameters. One of ordinary skill in the art of extracting a predictive model knows that the module-specific parameters may include the criteria of extraction, which is a design choice. Once the user determined that the mining results are satisfactory based on the user's queries or hypotheses, a predictive model is extracted based on such results (column 4, lines 42-57). Specifically, Simoudis et al. disclose the missing elements:

computer program code for selecting a group of attributes having a largest difference between the attribute values for the target group of samples and the attribute values for all samples (results, column 4, lines 48-51).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the teachings of Piatetsky-Shapiro to incorporate the teachings of Simoudis et al. to obtain the invention as specified in claim 25 because Simoudis et al. disclose details of a very flexible data mining method for generating predictive models to gain domain knowledge as Piatetsky-Shapiro suggested to improve a purely statistical prediction (page 230, line 26).

**4.** Claims 3-4, 16-17, and 23-24 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combined teachings of Piatetsky-Shapiro, "Discovery, Analysis, and Presentation of Strong Rules", in "Knowledge Discovery in Database", AAAI/MIT Press, 1991, and Simoudis et al., U.S. Patent No. 5,692,107 issued on November 25, 1997, and further in view of Dash et al., "Dimensionality Reduction of Unsupervised Data", Proceedings, Ninth IEEE International Conference on Tools with Artificial Intelligence, Nov. 1997.

**4-1.** Regarding claims 3 and 4, the combined teachings of Piatetsky-Shapiro and Simoudis et al. disclose determining a statistical measure of difference in claim 1. Piatetsky-Shapiro fails to expressly disclose:

(1) determining an entropy for the attribute values;

(2) identifying n attributes having a largest difference in respective values with said target population.

Nevertheless, Piatetsky-Shapiro does suggest that in addition to the exemplary simplest function, user-specified interest weights for different fields can also be considered (page 231, lines 26-27).

Dash et al. teach an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept for a task by choosing the first d variables if it is known that an application only needs d variables (section 2). Thus the user gains insight into the data after the important original features are known. Specifically, Dash et al. disclose the missing elements:

(claim 3) determining an entropy for the attribute values (equation (1), page 534);

(claim 4) identifying n attributes having a largest difference in respective values with said target population (choose the first d variables, page 535, column 1, second paragraph).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the combined teachings of Piatetsky-Shapiro and Simoudis et al. to incorporate the teachings of Dash et al. to obtain the invention as specified in claims 3 and 4 because Dash et al. disclose details of an entropy measure which is a user-specified rule-interest measure as Piatetsky-Shapiro suggested and may determine the relative importance of variables.

**4-2.** Regarding claim 16, the combined teachings of Piatetsky-Shapiro and Simoudis et al. disclose determining a statistical measure of difference in claim 15. Piatetsky-Shapiro fails to expressly disclose that the selection process determines an entropy for the attribute values.

Nevertheless, Piatetsky-Shapiro does suggest that in addition to the exemplary simplest function, user-specified interest weights for different fields can also be considered (page 231, lines 26-27).

Dash et al. teach an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept for a task by choosing the first d variables if it is known that an application only needs d variables (section 2). Thus the user gains insight into the data after the important original features are known. Specifically, Dash et al. disclose the missing element:

determines an entropy for the attribute values (equation (1), page 534);

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the combined teachings of Piatetsky-Shapiro and Simoudis et al. to incorporate the teachings of Dash et al. to obtain the invention as specified in claim 16 because Dash et al. disclose details of an entropy measure which is a user-specified rule-interest measure as Piatetsky-Shapiro suggested and may determine the relative importance of variables.

**4-3.** Regarding claim 17, the combined teachings of Piatetsky-Shapiro and Simoudis et al. disclose determining a statistical measure of difference in claim 14. Piatetsky-Shapiro fails to expressly disclose that the selection process identifies a predetermined number of attributes having a largest difference in the attribute values for selection.

Nevertheless, Piatetsky-Shapiro does suggest that in addition to the exemplary simplest function, user-specified interest weights for different fields can also be considered (page 231, lines 26-27).

Dash et al. teach an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept for a task by choosing the first d variables if it is known that an application only needs d

variables (section 2). Thus the user gains insight into the data after the important original features are known. Specifically, Dash et al. disclose the missing element:

identifies a predetermined number of attributes having a largest difference in the attribute values for selection (choose the first d variables, page 535, column 1, second paragraph);

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the combined teachings of Piatetsky-Shapiro and Simoudis et al. to incorporate the teachings of Dash et al. to obtain the invention as specified in claim 17 because Dash et al. disclose details of an entropy measure which is a user-specified rule-interest measure as Piatetsky-Shapiro suggested and may determine the relative importance of variables.

**4-4.** Regarding claim 23, the combined teachings of Piatetsky-Shapiro and Simoudis et al. disclose determining a statistical measure of difference in claim 22. Piatetsky-Shapiro fails to expressly disclose the determining and comparing entropy and comparing the relative measure of difference.

Nevertheless, Piatetsky-Shapiro does suggest that in addition to the exemplary simplest function, user-specified interest weights for different fields can also be considered (page 231, lines 26-27).

Dash et al. teach an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept for a task by choosing the first d variables if it is known that an application only needs d variables (section 2). Thus the user gains insight into the data after the important original features are known. Specifically, Dash et al. disclose the missing elements:

computer program code for determining an entropy of the attribute values for samples having the desired attribute value and an entropy of the attribute values for all samples (equation (1), page 534);

computer program code for comparing the entropy of the attribute values for samples having the desired attribute value to the entropy of the attribute values for all samples for each attribute to determine a relative measure of difference (ordered list, page 535, column 1, first paragraph); and

computer program code for comparing the relative measure of difference of all attributes (ordered list, page 535, column 1, first paragraph).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the combined teachings of Piatetsky-Shapiro and Simoudis et al. to incorporate the teachings of Dash et al. to obtain the invention as specified in claim 23 because Dash et al. disclose details of an entropy measure which is a user-specified rule-interest measure as Piatetsky-Shapiro suggested and may determine the relative importance of variables.

**4-5.** Regarding claim 24, the combination of Piatetsky-Shapiro and Simoudis et al. disclose determining a statistical measure of difference in claim 21. Piatetsky-Shapiro fails to expressly disclose the identifying n attributes having a largest difference in the attribute values.

Nevertheless, Piatetsky-Shapiro does suggest that in addition to the exemplary simplest function, user-specified interest weights for different fields can also be considered (page 231, lines 26-27).

Dash et al. teach an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept

for a task by choosing the first d variables if it is known that an application only needs d variables (section 2). Thus the user gains insight into the data after the important original features are known. Specifically, Dash et al. disclose the missing element:

computer program code for identifying n attributes having a largest difference in the attribute values (choose the first d variables, page 535, column 1, second paragraph).

It would have been obvious to one of ordinary skill in the art at the time the invention was made to modify the combined teachings of Piatetsky-Shapiro and Simoudis et al. to incorporate the teachings of Dash et al. to obtain the invention as specified in claim 24 because Dash et al. disclose details of an entropy measure which is a user-specified rule-interest measure as Piatetsky-Shapiro suggested and may determine the relative importance of variables.

***Applicants' Arguments***

**5.** Applicants argue the following:

**5-1.** "claims 22-24 have been amended to refer to the "computer program code" and it is believed that this Amendment overcomes the Examiner's rejection under U.S.C. § 112" (page 9, paragraph 2, paper # 16).

**5-2.** "the Shapiro reference is devoid of any teaching of the obtaining of a target population" (page 9, last paragraph, paper # 16) because "a summary of the sample population is not a target population" (page 10, last paragraph, paper # 16).

**5-3.** "Shapiro fails to teach or suggest in any way determining a statistical measure of difference between the attributes and the respective values of the target population and sample population as recited in claim 1" (page 10, last paragraph, paper # 16).

**5-4.** "Simoudis et al. do not teach "comparing said one or more desired attributes and respective values with said sample population to obtain a target population" (page 11, paragraph 2, paper # 16).

**5-5.** "Dash et al. is entirely silent on the subject of the reduction of variables based on a difference between the attributes and the respective values of a target group and sample population" (page 12, paragraph 2, paper # 16).

***Response to Arguments***

**6.** Applicants' arguments have been fully considered. They are not persuasive except for argument **5-1**. In summary, Examiner believes that all the claimed inventions have been disclosed by the combined teachings of Piatetsky-Shapiro, Simoudis et al., and Dash et al.

**6-1.** Response to Applicants' argument **5-1**. The original claim rejections under 35 U.S.C. 112, second paragraph, for indefiniteness have been withdrawn.

**6-2.** Response to Applicants' argument **5-2**. Applicants' argument appears to ignore the teachings of Piatetsky-Shapiro that the summary may preserve all of the field values and their relation to one another because "what intermediate information has to be kept is determined by the type of the summary description we want to have at the end" (page 236, lines 6-8). Therefore, one of ordinary skill in the art would be able to obtain a target population with one or more desired attributes and respective values, for example, A=a and B=b, by applying KID3 Algorithm and setting the summary to collect all the information of every sample which satisfying A=a and B=b within the sample population. In other words, Piatetsky-Shapiro does suggest how to obtain a target population, i.e., the summary, by applying the KID3 Algorithm.

**6-3.** Response to Applicants' argument **5-3**. Applicants' argument appears to ignore the teachings of Piatetsky-Shapiro that the rule-discovery task is to find K rules with the highest rule-interest function (page 231, line 28). Usually, the interest of rule A → B is computed as a function of p(A), the probability of A; p(B); p(A&B); or other parameters such as the domain sizes of A and B (page 231, lines23-26). The simplest function that Piatetsky-Shapiro suggested is $|A\&B| - (|A||B|/N)$ (page 232, line 18). Piatetsky-Shapiro also discloses how to precompute field statistics (page 230, line 19) to get information such as "How many samples satisfy the condition of C=c?" (page 233, lines 13-16) in the sample population. With these statistics, the cardinality |C| of conditions C=c can be estimated efficiently and accurately (page 233, lines 19-20). In other words, Piatetsky-Shapiro does suggest determining a statistical measure of difference between each of the attributes and respective values of the target population and sample population by applying the simplest function $|A\&B| - (|A||B|/N)$.

**6-4.** Response to Applicants' argument **5-4**. The Examiner acknowledges that Simoudis et al. do not expressly teach the comparing because Piatetsky-Shapiro has already taught it. However, Simoudis et al. disclose details of a very flexible data mining method for generating predictive models. The user may select a data analysis module from several different modules implementing different data mining techniques (column 3, lines 15-25) and set module-specific parameters (column 4, lines 45-48), for example, the criteria of extraction a predictive model, which is a design choice. Simoudis et al. also suggest that the data analysis modules may also be custom designed for specific applications (column 3, lines 26-27). Therefore, one of ordinary skill in the art would be motivated to select Piatetsky-Shapiro's KID3 Algorithm and calculate

the simplest function, |A&B| - (|A||B|/N), as the data analysis module to extract a predictive model by the teachings of Simoudis et al.

**6-5.** Response to Applicants' argument **5-5**. The Examiner does not use Dash et al. in the reduction of variables based on a difference between the attributes and the respective values of a target group and sample population because the teachings of Simoudis et al. has already disclosed it.

Dash et al. introduce an entropy measure for determining the relative importance of variables (section 2). Dash et al. also discloses a simple way to decide how many variables should be kept for a task by choosing the first d variables if it is known that an application only needs d variables (section 2). In other words, Dash et al. disclose a simple way to extract the first d most important variables by applying an entropy measure for determining the relative importance of variables. Extracting the first d most important variables implies the reduction of variables to only d variables.

### *Conclusion*

7. **THIS ACTION IS MADE FINAL**. Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37

CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

**8.** Any inquiry concerning this communication or earlier communications from the examiner should be directed to Herng-der Day whose telephone number is (703) 305-5269. The examiner can normally be reached on 9:00 - 17:30.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Kevin J Teska can be reached on (703) 305-9704. The fax phone numbers for the organization where this application or proceeding is assigned are (703) 746-7239 for regular communications and (703) 746-7238 for After Final communications.

Any inquiry of a general nature or relating to the status of this application or proceeding should be directed to the receptionist whose telephone number is (703) 305-3900.

Herng-der Day
August 11, 2003

KEVIN J. TESKA
SUPERVISORY
PATENT EXAMINER